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Review

Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles

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HIGHLIGHTS

- Most comprehensive and extensive review of methods for battery monitoring.
- More than 350 sources including scientific and technical literature are studied.
- Consideration of requirements on battery monitoring algorithms is included.
- Strengths and weaknesses of the methods are elaborated based on requirements.

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ABSTRACT

Lithium-ion battery packs in hybrid and pure electric vehicles are always equipped with a battery management system (BMS). The BMS consists of hardware and software for battery management including, among others, algorithms determining battery states. The continuous determination of battery states during operation is called battery monitoring. In this paper, the methods for monitoring of the battery state of charge, capacity, impedance parameters, available power, state of health, and remaining useful life are reviewed with the focus on elaboration of their strengths and weaknesses for the use in on-line BMS applications. To this end, more than 350 sources including scientific and technical literature are studied and the respective approaches are classified in various groups.

1. Introduction

Hybridization and electrification of vehicle propulsion systems have become key trends in the automotive industry in recent years. These trends are considered as primary instruments for increasing the total efficiency and decreasing or even eliminating carbon dioxide (CO_2) emissions and other pollutants from vehicles. Batteries form key components not only for pure battery electric vehicles (BEVs) but also for intermediate storage of electrical energy in fuel cell electric vehicles (FCEVs) and other hybrid EVs (HEVs). Currently only lithium-ion batteries (LIBs) are considered as a highly prospective technology for automotive applications because of its good

Abbreviations: AEKF, adaptive extended Kalman filter; ANFIS, adaptive neuro-fuzzy inference system; ANN, artificial neuronal networks; ASPKF, adaptive sigma-point Kalman filter; BEV, battery electric vehicle; BMS, battery management system; CDKF, central-difference Kalman filter; CPE, constant phase element; DCVP, discharging–charging voltage patterns; ECM, equivalent circuit model; EKF, extended Kalman filter; EMF, electromotive force; EMS, energy management system; FCEV, fuel cell electric vehicle; FPU, floating-point unit; GHQF, Gauss–Hermite quadrature filter; HEV, hybrid electric vehicles; KF, Kalman filter; LIB, lithium-ion battery; LMS, least mean squares (filter); LOLIMOT, local linear model tree; NCA, nickel–cobalt–aluminum-oxide (cathode material); NiMH, nickel–metal hydride (battery); NMC, nickel–manganese–cobalt (cathode material); OCV, open-circuit voltage; PDE, partial differential equation; PF, particle filter; PHEV, plug-in hybrid electric vehicle; RCP, rapid control prototyping (hardware, system); RLS, recursive least squares (filter, method); RUL, remaining useful life; RVM, relevance vector machine; SAVP, statistical analysis of voltage pattern; SOA, safe operating area; SoC, state of charge; SoF, state of function; SoH, state of health; SPKF, sigma-point Kalman filter; SVM, support vector machine; UKF, unscented Kalman filter; WRLS, weighted recursive least squares (filter, method).

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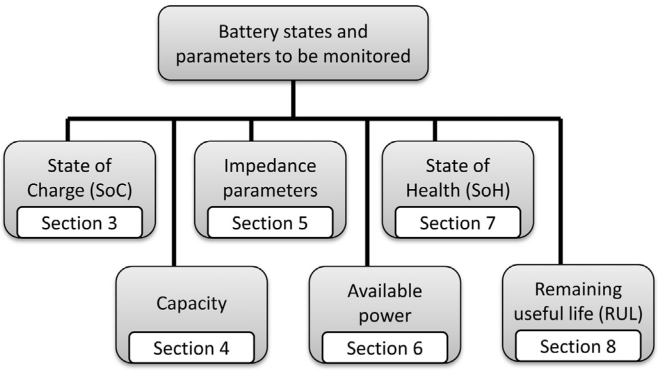

Fig. 1. Battery states and parameters to be monitored in electric and hybrid vehicles.

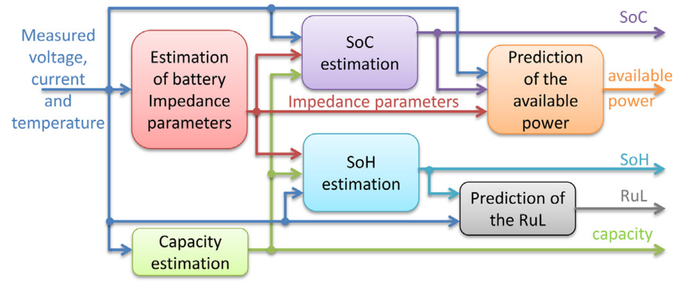

Fig. 2. A typical interaction and information flow between individual methods within of the battery monitoring system.

performance characteristics and promising potential for cost reduction [1,2].

LIB packs are always equipped with a battery management system (BMS). The BMS consists of hardware and software for battery management including, among others, algorithms determining battery states. The continuous determination of battery states during operation is called battery monitoring.

Since batteries are complex electrochemical devices with a distinct nonlinear behavior depending on various internal and external conditions, their monitoring is a challenging task. This task is additionally hindered by considerable changes in battery characteristics over its lifetime due to aging. On the other hand, very precise and especially reliable battery monitoring is a key function of the BMS. This function enables safe and reliable operation of the battery pack and, hence, of the total application where the battery pack is used. Therefore, special algorithms for battery monitoring are required. The requirements on battery monitoring algorithms are summarized in Section 2.

In next sections, the methods for the monitoring of battery states and parameters (Fig. 1) presented in scientific and technical literatures are reviewed.[1] The focus is to elaborate their strengths and weaknesses rather than to describe their respective approaches in detail. For detailed descriptions of the methods, the reader is advised to refer to the respective original sources referenced in this work or to the reviews that can be found in Refs. [3–22]. In the following sections, only methods that are applied or can be potentially applied for monitoring LIBs in BEVs and HEVs are considered. Some other methods specific for other battery technologies exist, e.g., lead-acid batteries or other applications, but their consideration lies beyond the scope of this paper.

The battery SoC can be employed in the figurative sense as a replacement for a fuel gauge used in conventional vehicles. The SoC is basically the relationship between the residual battery capacity in its present state (C_r) and total capacity C_{bat} after completely charging the battery, expressed in a percentage: $SoC = C_r/C_{bat} \cdot 100\%$. Methods for the SoC monitoring are considered in Section 3 and methods for the estimation of the total battery capacity in Section 4.

For EV applications, batteries must not only deliver a certain amount of energy to the drive train during operation but also provide a certain power in various situations. The battery's capability to fulfill certain tasks is often referred to as the state of function (SoF). For the energy management system (EMS) operating in EVs, knowing the maximum power that can be applied to and from the battery by charging or discharging, respectively, is essential. This power depends, among others, on the present battery impedance characteristics. The methods for the estimation of the battery impedance and for the prediction of the available power are considered in Sections 5 and 6, respectively.

The capability of the battery to store energy and provide a certain power decreases over the battery lifetime because of aging. As an indicator for this deterioration, the additional battery state—state of health (SoH)—is defined. The methods for its determination are considered in Section 7.

The final battery state of interest is the remaining useful life (RUL). As RUL usually the remaining time or number of load cycles until the battery reaches its end of life (EoL) is understood. The methods for the RUL estimation are considered in Section 8.

A typical interaction and information flow among individual methods within of the battery monitoring system is shown in Fig. 2.

2. Requirements on battery monitoring algorithms

In this section the requirements on battery monitoring algorithms are given (Fig. 3). First, the battery monitoring algorithms have to consider battery characteristics. One challenge is that battery characteristics depend significantly on the battery internal and external conditions (for example, SoC, temperature, current). The other challenge is that almost all battery characteristics, including, for example, battery capacity and impedance parameters, changes significantly over the battery lifetime due to aging [23].

Second, the battery monitoring algorithms have to consider strong limitations regarding the operating conditions of LIBs. The

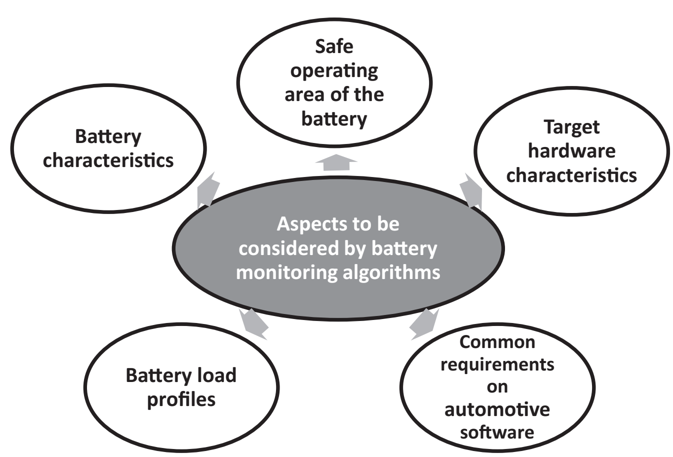

Fig. 3. Requirements on battery monitoring algorithms.

[1] This review is based on the Ph.D. thesis of Wladislaw Waag submitted to Faculty of Electrical Engineering and Information Technology at RWTH Aachen University in October 2013.

safe operating area (SOA) of LIBs is formed by the following boundaries:

- maximum discharge current and maximum charge current,
- minimal and maximal voltages for each individual cell, and
- maximum and minimum temperature.

These limits play a significant role for the calculation of the available energy and power. Some of the limits are usually fixed (e.g., minimal and maximal voltages, maximal temperature). Other limits might depend on battery conditions. For example, the maximum charge current might depend on the temperature, which must be decreased at low temperatures to prevent lithium plating.[2] All limits imposed for cell operation conditions must at least consider the requirements defined by the cell manufacturer. In addition, regarding the SOA, other limits might be defined or existing limits might be tightened to prevent excessive aging. For example, the maximum SoC can be limited.

Third, the characteristics of the target hardware, including the measuring system and microcontroller for the execution of the algorithms, must be considered. Only battery current, voltage and temperature are accessible for low-cost measurement. The limitations regarding the accuracy of the measurement system have to be taken into account. While the total pack voltage and single cell voltages can be measured very accurately and with a high degree of cost-efficiency, an accurate low-cost measurement of the battery current is still a challenge. Especially offset errors in current measurement have to be considered. The other substantial aspect to be considered is the computing power and available memory of the target microcontroller. One common characteristic of cost-efficient microcontrollers is the absence of the floating-point unit (FPU) because the integration of the FPU into the microcontroller always increases its cost. In consideration of this fact, monitoring algorithms must be easily convertible to a fixed-point implementation to avoid floating-point emulation that is always computationally intensive. To this end, the monitoring algorithms must be numerically robust because numerical deficiencies are exacerbated by the conversion of the algorithms into fixed-point.

Fourth, the influences of the battery load profiles must be considered. The monitoring algorithms can learn about the battery states considering the measured signals (current, voltage, temperature). These signals are defined not only by the battery but also by the load profile and may be very different depending on the battery load. High battery load, for example, may cause a rapid temperature changes and, therefore, may lead to an inhomogeneous temperature distribution within each cell, which, in consequence, may lead to local SoC differences in cell electrodes, as demonstrated in Ref. [24]. Such effects complicate battery monitoring.

Fifth, the common requirements on automotive software must be considered. These requirements include, among others, the requirement for traceable software. In case of a malfunction or unforeseeable results, reproducing them and understanding the source of the problem must be possible. Therefore, the usage of non-deterministic algorithms must be limited whenever it is possible.

All these requirements lead to the need for the development of battery monitoring algorithms that represent a certain compromise between accuracy, robustness, adaptiveness, and applicability on low-cost target hardware.

[2] Lithium plating is the deposition of lithium-ions on the anode as metallic lithium [375].

3. Methods for the SoC estimation

As mentioned in the introduction, the SoC of the battery in EVs can be employed as a replacement for a fuel gauge used in conventional vehicles. Therefore, the determination of the battery SoC is always a part of the BMS. Therefore, there are a wide range of approaches proposed in the literature, most of which are considered in the following sections (see also Fig. 4).

3.1. Ampere-hour counting

When the battery capacity is known and battery current can be measured precisely, ampere-hour counting permits the accurate calculation of changes in the SoC. This method works very accurately for LIBs because there are no significant side reactions during normal operation. However, for the estimation of the SoC by this method, the initial SoC must be known. Furthermore, when ampere-hour counting is performed over a long period of time, accumulated measurement errors might be a source of significant inaccuracy and an additional recalibration might be required. Therefore, ampere-hour counting is used only in combination with other supporting techniques, for example, with an OCV-based SoC estimation. An example of other possible supporting techniques is power analysis [25] or SoC estimation based on the calculation of the battery resistance [26]. However, both techniques have all disadvantages of impedance-based SoC estimation approaches described in Section 3.4.

The ampere-hour counting method requires knowledge of the present battery capacity. For some battery technologies, the battery capacity not only depends on the battery conditions at the end of discharge, but also on the current rates during the complete discharging process (short-time discharge history). For these cases, some approaches for the correction of the ampere-hour counter are proposed in the literature, for example, in Refs. [27,28]. The capacity of LIBs is practically independent of the short-time discharge history and is only defined by the current and temperature at the end of discharge. Therefore, ampere-hour counting can be performed as related to the battery capacity at nominal conditions and can be at any time recalculated to any other capacity if required.

In summary, ampere-hour counting can be concluded to be a good basis for the estimation of the SoC of LIBs in BEVs and HEVs for the following reasons:

- low-cost sensors for current measurement are available,
- the required computing power is very low, and
- combination with other techniques is possible.

3.2. OCV-based estimation

The relationship between the battery OCV and SoC is exploited for the estimation of the SoC for all battery technologies. It can be efficiently used for LIBs in BEVs and HEVs because of the following reasons:

1) Many HEVs and BEVs are driven only for some hours per day, and they are later charged within some hours. Therefore, the battery exists under open-circuit conditions for a sufficient time to enable an accurate OCV measurement. Some HEVs and BEVs might be driven often, and there might be only very short periods of time to measure the battery OCV. The measured OCV might be therefore “disturbed” by battery overvoltages that decline slowly after current interruption. However, a number of methods exist to consider OCV relaxation and to predict the “pure” battery OCV required for an accurate SoC estimation. These approaches are considered in Section 3.2.1.

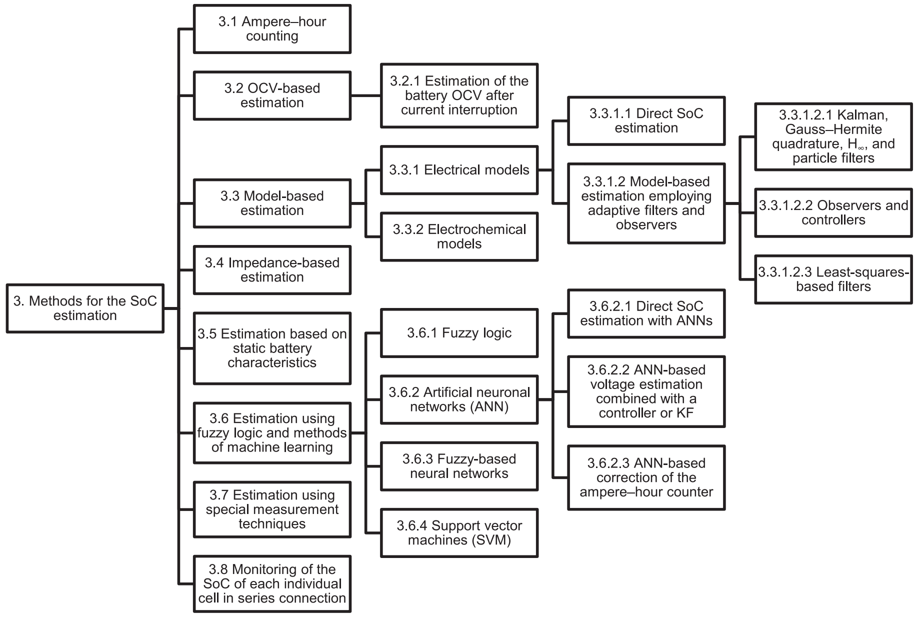

Fig. 4. Classification of the methods for the SoC estimation.

2) The OCV–SoC relationship is very distinct for the majority of LIB chemistries including batteries having a nickel–manganese–cobalt (NMC) or nickel–cobalt–aluminum-oxide (NCA) cathode. The exception is, for example, batteries having a $LiFePO_4$ cathode. The other advantage is that the OCV–SoC relationship changes only slightly over the battery lifetime. This change can be neglected.
3) The OCV hysteresis can be neglected at moderate and high temperatures except for batteries with a $LiFePO_4$ cathode. When required, an additional hysteresis model can be integrated, as, for example, proposed in Refs. [29–31] for nickel–metal hydride (NiMH) batteries. However, the usage of a hysteresis model might require complex model-based approaches for the SoC estimation, as described below in Section 3.3.

Considering these aspects and advantages of ampere-hour counting, the combination of the OCV- and ampere-hour counting-based methods is apparently a very simple and an efficient approach for the SoC estimation of LIBs in BEVs and HEVs.

3.2.1. Estimation of the battery OCV after current interruption

As described above, for an accurate SoC estimation, the prediction of the battery "pure" OCV (when all overvoltages are declined) is advantageous. In the following, a distinction is drawn between the battery OCV and EMF: any battery voltage measured under open-circuit condition is called OCV, and the equilibrium battery voltage at the end of OCV relaxation ("pure" OCV) is called EMF. OCV relaxation is the change in the battery OCV after current interruption. It is mainly dominated by diffusion processes and may take up to several hours; especially when the battery is almost empty, at low temperatures and after charging or discharging with high current rates.

There are some approaches presented in the literature to estimate the battery EMF by considering OCV relaxation over only a limited period of time.

In Ref. [32], the EMF of a LAB is predicted by an on-line approximation of the OCV relaxation curve by two asymptotes when plotted on a semi-log scale: $V_{OCV} = f(\log(t))$. A set of parameters is employed to estimate the battery EMF by consideration of these asymptotes. These parameters are found from previous laboratory experiments on a new battery. The disadvantage of the method is that when the battery ages, the parameters used to describe the voltage relaxation process become increasingly less accurate. The result is a decrease in the accuracy of the EMF estimation.

Another method is presented in Ref. [33]. It uses an empirical equation to predict the EMF by measuring the battery OCV (V_{OCV}), OCV slope (dV_{OCV}/dt), and temperature: $\mathrm{EMF} = a \cdot V_{OCV} + b \cdot (dV_{OCV}/dt) - c \cdot T - d$. The parameters a, b, c, and d are found by previous laboratory experiments. However, similar to the method described previously, the accuracy of this method gradually diminishes during the aging of the battery because the applied parameters become increasingly inaccurate.

To overcome the problem associated with a decline in parameter accuracy with battery aging, completely adaptive methods are developed in Refs. [34–38]. The general idea is to have a model of OCV relaxation that includes the EMF and to observe OCV relaxation each time the current is interrupted. After a short observation, the model parameters are determined, for example, by fitting the model to the measured OCV relaxation curve; thus, the EMF is estimated. As a voltage relaxation model, an exponential function is used in Ref. [36]:

$$V_{OCV}(t) = \mathrm{EMF} - (\mathrm{EMF} - V_{OCV}(t = 0)) \cdot e^{-t/\tau}. \tag{4.1}$$

The advantage of this simple function is that its parameters EMF and τ can be determined very easily. The disadvantage is that it approximates the OCV relaxation very inaccurate, as shown in Ref. [38].

In Refs. [34,35], a more complex empirical model is introduced to describe OCV relaxation of LIBs:

$$V_{OCV}(t) = \mathrm{EMF} - \frac{\gamma}{t^{\alpha} \cdot \log^{\beta}(t)}. \tag{4.2}$$

In Ref. [35], for one particular battery type (1.1 Ah battery of type US18500G3 manufactured by Sony), this function is shown to approximate the OCV relaxation curve very accurately. However, as shown in Ref. [38], reproducing this high accuracy when Eq. (4.2) is

applied, for example, to a LIB with NMC cathode material may be impossible. Unfortunately, the authors of [34,35] do not explain if the function in Eq. (4.2) is obtained empirically or based on a theoretical analysis of the battery EMF. Therefore, proving whether this approach can be transferred to other LIBs is impossible. In Ref. [37], however, the same model (but employing different technique to fit the model on-line to the measured OCV relaxation) is applied successfully on other cell type.

An alternative, completely adaptive approach is proposed in Ref. [38]. In this work an OCV relaxation model based on theoretical consideration of the battery diffusion is proposed and successfully applied for the fast estimation of the battery EMF after current interruption. The model is shown to be very accurate. The application for the estimation of the battery SoC and capacity is demonstrated including consideration of the real-time capability of the algorithm by its implementation on a low-cost microcontroller.

3.3. Model-based estimation

The main idea of the model-based SoC estimation is to connect the measured battery signals (voltage, current, and temperature) with the battery SoC employing a battery model. By measuring the battery on-line and using the signals as model inputs, a model can be used to calculate the SoC. The following two types of battery models are employed: electrical and electrochemical models.

3.3.1. Electrical models

An electrical model is the most popular model type for model-based SoC estimation. For example, an equivalent circuit model (ECM) can be used, as shown in Fig. 5. Alternatively, the model can be a pure mathematical model, as, for example, proposed in Ref. [39]. In both cases, the model is represented in the form of one or more equations that employ electrical quantities. The battery SoC can be directly incorporated into the model using its relationship with the battery OCV. A possible variation is not to incorporate the battery SoC, but to estimate the battery OCV using the model and then use the OCV–SoC relationship to calculate the estimated SoC from the OCV.

In any case, the core of the model-based SoC estimation using an electrical model is the estimation of the battery OCV by measuring the battery voltage, current, and temperature.[3]

The common disadvantage of all SoC estimation methods based on electrical models is that the model parameters can only be parameterized accurately for new batteries in the laboratory. Adaption of the model parameters over the battery lifetime to any given battery aging state requires complex algorithms and is practical for only quite simple models. The common advantage is that the SoC can be estimated at any battery condition during charging or discharging as long as the employed battery model is able to reproduce the battery behavior at this condition.

3.3.1.1. Direct SoC estimation. Employing simple models, the SoC can be directly calculated by the transformation of the model equations, as, for example, proposed in Refs. [40–43]. This approach is generally described as an open-loop method. The advantage of this approach is its simplicity that enables easy implementation on a low-cost target microcontroller. The

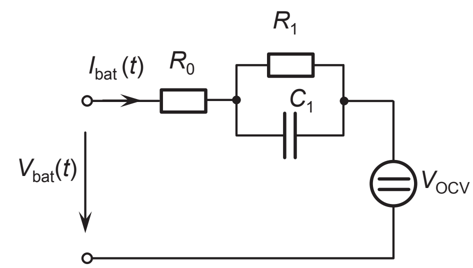

Fig. 5. An example of the equivalent circuit model (ECM) that can be used for the model-based SoC estimation.

disadvantage, beside the common disadvantage of all model-based methods as described above, is low accuracy because the model is expected to exactly reproduce the behavior of the battery and there is no possibility to consider the inaccuracies inherent in the model itself.

3.3.1.2. Model-based estimation employing adaptive filters and observers. To improve the accuracy of model-based SoC estimation and to make the estimation possible when complex models are used, adaptive techniques known from control theory are employed. Using these techniques, closed-loop estimation can be implemented, wherein the deviation between the modeled and measured battery voltages is used for the correction of the estimated states. In this way, the influence of the inaccuracy of the model and that of the measured battery signals on the result is reduced.

3.3.1.2.1. Kalman, Gauss–Hermite quadrature, H_∞, and particle filters. The most widely used adaptive filter technique is the Kalman filter (KF) [44]. The first application of the KF for monitoring batteries can be found in Ref. [45]. The ordinary KF is used with rather simple and linear models [45–59], whereas the modern extensions of the KF permit the usage of more complex and nonlinear models. The first advanced type is the extended KF (EKF). It is used in different variations and with various battery models, e.g., in Refs. [39,60–101].

The disadvantage of the EKF is that it linearizes battery model nonlinearities; therefore, it is not very accurate. In addition, it also may lack robustness. Better consideration of model nonlinearities can be achieved employing a sigma-point KF (SPKF). The different forms of this filter, including the unscented KF (UKF) and central-difference KF (CDKF), are used, e.g., in Refs. [74,78,102–110]. An alternative to the SPKF is the Gauss–Hermite quadrature filter (GHQF). It is generally similar to the SPKF and has been proposed for the estimation of the SoC in Ref. [111].

When the battery model includes fractional-order elements, such as the constant phase element (CPE) [112], a fractional-order KF must be applied, as, for instance, is done in Ref. [113].

All KF variants require knowledge of model and measurement noises covariances. Inaccurate knowledge of these factors can lead to either poor convergence or excessively slow adaption. The adaptive KF (AKF) [114], the adaptive EKF (AEKF) [115–123] or adaptive SPKF (ASPKF) [124] is used to estimate the model and measurement noises covariances on-line at the expense of additional computing power. Another EKF-based method for the SoC estimation is presented in Ref. [125]. The authors claim its strong robustness against model uncertainties. The other solution is to use the H_∞ (H-infinity) filter, as proposed in Refs. [126–129]. In contrast to the KFs, the H_∞ filter does not require any assumptions concerning model and measurement uncertainties.

The other problem associated with model and measurement noises is that they are assumed to be Gaussian. However, this

[3] However, it does not necessarily mean that the real OCV–SoC relationship is used for the parameterization of the model. This relationship can be a part of the model; therefore, it is represented by some parameters. These parameters can be determined using different parameterization techniques and optimized to reproduce the battery voltage under typical operating conditions.

assumption obviously does not relate well to real applications. Although the KF has been shown to be stable when noises are not exactly Gaussian, this fact always has a negative influence on the convergence behavior and accuracy of the filter. To avoid this, a particle filter (PF) is employed in Refs. [130–132] and an unscented particle filter (UPF) in Refs. [133,134] for the estimation of the SoC. These filters require very high computing power (by factor 50 compared, for example, to the UKF as shown in Ref. [133]) and memory consumption, but results in a rather moderate improvement compared to KFs.

Another complication that must be considered using KFs is that the battery model might not be completely observable under some conditions: for example, when the battery current is constant. This problem is considered and a respective solution is proposed in Refs. [135,136].

The main advantage of KF-based SoC estimation is that it can be performed very accurately and continuously during battery operation. The precondition, however, is the adoption of a comprehensive and well-parameterized battery model. In Ref. [94], for example, it is shown that the performance of the KF-based SoC estimation decreases considerably if the model parameters are not very accurate. The parameterization can be performed very accurately in the laboratory for new cells. To consider the change of model parameters over the battery lifetime, joint or dual KFs can be employed, as will be described in Section 5. However, the robust estimation of model parameters is possible only for relatively simple models. The usage of simple models, on the other hand, leads to higher inaccuracy of the SoC estimation.

The main disadvantage of KF-based SoC estimation is the high demand on computing power. The calculations involve complex matrix operations (e.g., matrix inversion) that can lead to numerical instabilities and additionally complicates the implementation of the algorithm on an ordinary, low-cost microcontroller.

3.3.1.2.2. Observers and controllers. A number of various approaches employing observers and controllers for closed-loop model-based SoC estimation can be found in the literature (Table 1). From all these approaches, the most promising are the methods presented in Refs. [15,144,145,148,149,153–155]. All these methods combine an ampere-hour counting approach with a computationally simple observer or controller. The simplicity and sufficient accuracy of these methods is advantageous. The precondition for an accurate estimation over the total battery lifetime, however, is an additional algorithm that adapts the parameters of the employed battery model to the present aging state of the battery. This adaption is considered only in the methods presented in Refs. [15,148,153–155].

A very simple approach is proposed in Refs. [161,162], and it is used in Ref. [163]. The battery current and voltage are observed over a short period of time. A battery model with the OCV and series resistance as free parameters is fitted to these measured data using an ordinary least-square approach. As a result, the OCV is determined and is used for the estimation of the SoC. Unfortunately, the approach cannot apparently be used when the battery SoC changes rapidly. Furthermore, the parameters of the employed model (except the series resistance) are constants and parameterized only for a new battery. Therefore, the accuracy of the method decreases over the battery lifetime.

3.3.1.2.3. Least-squares-based filters. In Refs. [164–166], a recursive least-squares (RLS) filter is employed for the SoC estimation. KFs and other filters mentioned in Section 3.3.1.2.1 consider the input signals as stochastic, whereas the RLS filter considers them as deterministic. This is more convenient with respect to battery monitoring because low-cost measuring hardware is available for the low-noise battery current and voltage measurements. Therefore, the main challenge for an adaptive filter is not to deal with stochastic measurement noises but with the inaccuracy of the deterministic battery model.

The advantage of the RLS algorithm for the estimation of the SoC is that it does not require complex matrix operations such as inversion; therefore, it can be efficiently implemented on a low-cost microcontroller. Furthermore, it permits simultaneous estimation of the model parameters to consider their change over the battery lifetime. The disadvantage is that the algorithm may suffer from significant divergence problems when the battery model

Table 1
Observers and controllers employed for closed-loop electrical model based SoC estimation.

Method description	References	Is a combination with the ampere-hour counting method applied?	Is the adaption of the model parameters to the present aging state of the battery considered?
Sliding mode observer	[137–141]	No	No
Adaptive switching gain sliding mode observer	[142,143]	No	No
Integral controller in combination with the ampere-hour counting method	[144,145]	Yes	No
Special observer including Lyapunov-based stability analysis	[146]	No	No
Luenberger observer	[74,139,147]	No	No
Observer for the OCV hysteresis in combination with an ampere-hour counter and with the direct calculation of the overvoltages using a battery impedance model	[15,148]	Yes	Yes
Unspecified controller using an electrical model including the temperature as an input combined with an ampere-hour counter	[149]	Yes	No
Reduced-order observer	[150]	No	No
Adaptive observer	[151]	No	No
Adaptive observer based on the Lyapunov-stability criteria	[152]	No	No
Ampere-hour counter with a correction performed by the OCV observer that includes the direct calculation of the overvoltages using a battery impedance model	[153–155]	Yes	Yes
Adaptive subspace identification method	[156]	No	No
Method based on a linear parameter varying system technique	[157]	No	No
Method based on a polynomial approach	[158]	No	No
Nonlinear observer based on the Levenberg–Marquardt algorithm	[159]	No	No
Hybrid observer with a piecewise linearization of the OCV–SoC relationship (applied on NiMH battery, but also potentially applicable on LIBs)	[160]	No	No

inaccurately reproduces the battery behavior. The other disadvantage is that the RLS filter cannot be efficiently used with strongly nonlinear battery models.

In Refs. [167,168], a moving window least-squares filter is employed for the SoC estimation. The first advantage is as of the RLS algorithm: it estimates simultaneously the model parameters to consider their change during battery operation. The other advantage is that the method has better stability. This is achieved, however, at the expense of higher demand on computing power and memory consumption for intermediate storage of the measured data.

3.3.2. Electrochemical models

As an alternative to electrical models, electrochemical models can be used for model-based SoC estimation (Table 2). The advantage of electrochemical models is that they inherently include the dependence of the battery behavior on the SoC and temperature, while electrical models must store their parameters as look-up tables for various SoC and temperature combinations. The disadvantage of electrochemical models is their high complexity. This complexity not only does prevent implementation of monitoring algorithms on low-cost target microcontrollers but also reduces the number of model parameters that can be adapted on-line to the present aging state of the battery. This adaption is only considered in Refs. [173,174,178,180,181,183,184].

3.4. Impedance-based estimation

The dependence of some battery impedance parameters on the SoC has encouraged many researches to use them as a basis for the estimation of the SoC of lead-acid, NiMH, nickel–cadmium, and LIBs [185–200]. However, as shown for example, in Ref. [23], the dependence of the battery impedance parameters on the SoC significantly changes over the battery lifetime for LIBs. Therefore, these impedance parameters alone cannot be good indicators of the SoC as the battery ages.

The other disadvantage is that the sensitivity of the impedance parameters on the SoC is much lower than that on the temperature. Therefore, a very accurate measurement of the temperature is required to compensate for its influence. However, such accuracy is not always possible for batteries in BEVs and HEVs because the battery temperature might change very rapidly, and temperature gradients in the battery pack or even within single cells may occur, as discussed in Section 2.

3.5. Estimation based on static battery characteristics

When the battery load remains constant over a sufficient period of time, the relationship among the battery current, voltage, and temperature can be used to estimate the SoC. For example, in Ref. [201], the battery SoC is proposed to be estimated by observing the battery voltage and current during constant current charging. The function SoC $= f(V_{\mathrm{charge}}, I_{\mathrm{charge}})$ is parameterized for a new battery and stored as a look-up table in the BMS. In Ref. [202], a special parameter—the ramp peak current—is calculated on-line and employed for the SoC estimation using a static look-up table.

Such approaches are practically inapplicable for LIBs in BEVs and HEVs. First, the battery load in the vehicle is very dynamic. Second, the parameterized look-up tables are valid only for the new cells used for their parameterization. The aging of the battery cannot be considered.

3.6. Estimation using fuzzy logic and methods of machine learning

In this section, the application of fuzzy logic, artificial neuronal networks (ANN), fuzzy-based neural networks, and support vector machines (SVMs) for the estimation of the SoC is considered.

3.6.1. Fuzzy logic

Fuzzy logic can be used as an extension of other SoC estimation techniques. In Refs. [198,199,203], fuzzy logic is used to connect the battery SoC with the impedance parameters. The proposed SoC estimation is therefore, basically, based on impedance (Section 3.4). Fuzzy logic is also used in Refs. [204,205] to connect the battery SoC with the measured battery current, voltage and temperature. The proposed SoC estimation is therefore, basically, based on static battery characteristics (Section 3.5). In all cases, the resulting methods have all disadvantages of the respective underlying methods.

3.6.2. Artificial neuronal networks (ANN)

All methods for the estimation of the SoC employing ANN can be roughly divided into the following three groups: direct SoC estimation with ANNs, ANN-based voltage estimation combined with a controller or KF, and ANN-based correction of an ampere-hour counter.

3.6.2.1. Direct SoC estimation with ANNs. Direct SoC estimation with ANNs is employed, for example, in Refs. [206–217]. The approaches of these estimation methods are generally similar to that of the direct model-based SoC estimation method described in Section 3.3.1.1. The difference is that the battery SoC is modeled by an ANN rather than by a deterministic electrical model. The advantage of the ANN-based model is that no exact knowledge about the behavior of the battery is required. However, a significant amount of data is required to train the ANN. Furthermore, the ANN trained for a new battery cannot be accurate for an aged battery. Because of the open-loop character of this approach, on-line training of the ANN and, therefore, its adaption to the aging state of the battery is not possible.

3.6.2.2. ANN-based voltage estimation combined with a controller or KF. Closed-loop SoC estimation using ANNs is implemented in Ref. [218] by applying a neuro-controller and, in Refs. [219–221], by

Table 2
Methods employed for the closed-loop electrochemical model-based SoC estimation.

Method description	References	Is the adaption of the model parameters to the present aging state of the battery considered?
Electrochemical model of the LIB in combination with an ordinary KF	[169]	No
Electrochemical model of a NiMH battery in combination with the EKF	[170]	No
Various electrochemical models of LIBs in combination with the EKF	[171–176]	Only in Ref. [174]
Electrochemical models of LIBs in combination with the SPKF	[173,177,178]	Only in Refs. [173,178]
Electrochemical model of the LIB in combination with the output injection-based PDE observer	[179]	No
Electrochemical model of the LIB in combination with the backstepping PDE observer	[180–183]	Yes
Electrochemical model of the LIB in combination with the multi-rate particle filter	[184]	No

applying the EKF. In Ref. [222] the closed-loop SoC estimation is implemented applying the ANN-based extreme learning machine (ELM) in combination with the EKF. In all these approaches, the estimated SoC is used as one of the inputs of the ANN. The output is the battery voltage and is compared to the measured battery voltage. The difference is used to correct the SoC estimation.

The advantage of this closed-loop approach is that it theoretically permits training of the ANN on-line during battery operation. In this way, the ANN can be adapted to the present aging state of the battery. However, such on-line training requires high computational effort and brings various potential problems, such as overfitting, that must be managed.

The usage of an ANN-based model in combination with an adaptive filter or controller can be advantageous if the battery behavior cannot be accurately modeled with a simple electrical model. This is the case for lead-acid or NiMH batteries rather than that for LIBs. The usage of a deterministic electrical model is preferred when better control over the model behavior is required.

3.6.2.3. ANN-based correction of the ampere-hour counter. In Refs. [223,224], the ANN is applied for a LAB and, in Ref. [225], for a Na–$NiCl_2$ (ZEBRA) battery to improve the accuracy of the ampere-hour counter. Therefore, the ANN models the dependence of the battery capacity and/or charge/discharge efficiency on the temperature and short-time load history. Since the coulombic efficiency of LIBs is nearly 100% and the capacity practically does not depend on the short-time load history, this type of correction of the ampere-hour counter is not required.

3.6.3. Fuzzy-based neural networks

The following two types of fuzzy-based neural networks are used in the literature for the estimation of the SoC: the adaptive neuro-fuzzy inference system (ANFIS) in Refs. [226–232] and the local linear model tree (LOLIMOT) in Ref. [233].

In all cases direct, open-loop SoC estimation is implemented. Therefore, the approach of this estimation is basically the same as that of the direct SoC estimation using ANNs (Section 3.6.2.1) and has the same disadvantages.

3.6.4. Support vector machines (SVM)

Similar to the direct SoC estimation using ANN (Section 3.6.2.1) and fuzzy-based neural networks (Section 3.6.3), the SoC estimation employing the SVM method is implemented, for example, in Refs. [234–240]. In the same manner as neural networks, the SVM requires extensive training; therefore, it has the same disadvantages as those of the direct SoC estimation using ANNs (Section 3.6.2.1).

3.7. Estimation using special measurement techniques

In a conventional BMS, only the battery current, voltage, and temperature are available for measurement. In Refs. [241–245], the usage of an additional sensor for the measurement of the battery magnetic characteristic is proposed. The magnetic characteristic is determined to change with the battery SoC; therefore, it can be used as a SoC indicator. Unfortunately, whether the magnetic characteristic changes over the battery lifetime and how the respective recalibration can be performed if required is not shown.

The other disadvantage is the need for an additional sensor. The sensor itself would be quite expensive even in mass production because it includes hardware for an active generation of a high frequency magnetic field. High costs for the sensor in combination with moderate accuracy prohibit the wide usage of this method.

3.8. Monitoring of the SoC of each individual cell in series connection

In a lithium-ion battery pack usually many cells are connected in series. One approach to estimate the SoC of each individual cell is to apply one of the methods described in previous sections on each cell separately. The disadvantage is the high demand on computing power, especially if sophisticated methods such as Kalman filter are used. Therefore, some alternatives are proposed in the literature.

In Ref. [104], the bar-delta filtering is introduced. While the pack-average SoC is estimated applying the more sophisticated SPKF-based method, the SoC of each individual cell is estimated employing simplified EKF-based algorithm. The simplification is possible because only the difference to the pack-average SoC is estimated for each individual cell and this difference is assumed to be small. As a result, the estimation of the SoC of each individual cell is possible with sufficient accuracy and with significantly lower demand on computing power compared to application of the sophisticated SoC estimation method separately on each individual cell.

Similar approaches are employed in Refs. [15,64,153,246]. In Refs. [15,153], the Luenberger observer is employed to estimate the pack-average SoC. Additionally, some simple calculations are performed to estimate the differences between the SoC of each individual cell and the pack-average SoC. A sophisticated EKF is employed in Ref. [64] to estimate the pack-average SoC and single-state EKFs are employed to estimate the differences between the SoC of each individual cell and the pack-average SoC. In Ref. [246] a quite sophisticated cell mean model and very simple cell difference model are introduced. The cell difference model considers the difference in OCV and battery resistance of each individual cell. These differences are estimated employing the least squares algorithm.

A completely different approach is proposed in Ref. [159]. The SoC estimation method introduced in this work permits determination of the SoC of each individual cell under reduced voltage sensing. Only the total battery pack voltage is required to be measured, no individual cell voltages. It is shown to work for two lithium iron phosphate cells in series connection for high and low SoC. The method cannot be applied for middle SoC and for many other lithium-ion battery technologies because it requires strong non-linear OCV–SoC relationship. The other disadvantage is that the method requires quite high computing power. Furthermore, it is questionable if it can be reliably applied for more than two or three cells connected in series.

4. Methods for capacity estimation

The battery capacity is a figure of merit determining the energy that is stored in the battery and is available for usage when the battery is fully charged. The capacity of the particular battery or cell in a new state is defined by the battery or cell design and varies only slightly for individual batteries or cells of a given type because of the production tolerances. Over the battery lifetime, however, the capacity changes considerably due to aging processes. Therefore, the present capacity of the battery must be determined by the monitoring algorithms.

When the battery is being charged or discharged, its voltage generally increases or decreases, respectively. The discharging or charging of a certain amount of ampere-hours creates a higher voltage change for a battery with a lower capacity than that for a battery of the same type but with a higher capacity. Therefore, the battery capacity can be considered as a parameter defining the relationship between the ampere-hours charged or discharged from the battery and voltage difference before and after the

respective charging or discharging. The determination of this relationship is therefore the basic principle of almost all methods for on-board capacity estimation (Fig. 6). The differences among single approaches consist only in how the voltage change is measured and correlated with the charged or discharged ampere-hours. All methods presented in the literature can be generally divided into four groups.

The methods from the first group consider the change in the measured battery OCV before and after charging or discharging [3,35,68,247–257]. The battery capacity is calculated on the basis of the OCV–SoC relationship for the given battery type. The advantage of these methods is that only the SoC–OCV relationship is used as a parameter. Its variation is small over the battery lifetime. Therefore, the accuracy of the method for aged batteries is almost as high as that for new batteries. The disadvantage is that the OCV has to be measured at two very different SoC levels for accurate capacity estimation. If batteries in BEVs are always charged immediately after being discharged during driving, there might be no opportunity to accurately measure the battery OCV at low SoC (because sufficient time is required for overvoltages to decrease after discharging).

The methods from the second group [258–260] estimate the OCV change from the battery voltage measured under load. The advantage is that the capacity can be estimated each time the battery is sufficiently discharged or charged. The disadvantage is that an accurate OCV estimation from the battery voltage measured under load might be a very challenging task and requires an accurate battery model with parameters adaptable to the aging state of the battery.

The methods from the third group augment the electrical battery model to include information about the battery capacity in the form of a parameter. One of the adaptive techniques is used to simultaneously estimate the battery SoC (directly or indirectly through the estimation of the OCV) and model parameters. This is called joint estimation. In Refs. [60,61], the EKF, in Ref. [107], the UKF, and, in Refs. [261,262], the RLS algorithm is employed. These methods can potentially estimate the capacity as accurately as the battery is modeled, and the SoC is thereby estimated. Similar to the other methods, these methods require a significant change in the battery SoC to accurately estimate the capacity. The disadvantage is the high complexity (large matrix operations, including inversions), especially for the joint KF operations, due to the high dimension of the resulting augmented model. Furthermore, the joint estimation may suffer from instability and has potentially poor numerical conditioning [263].

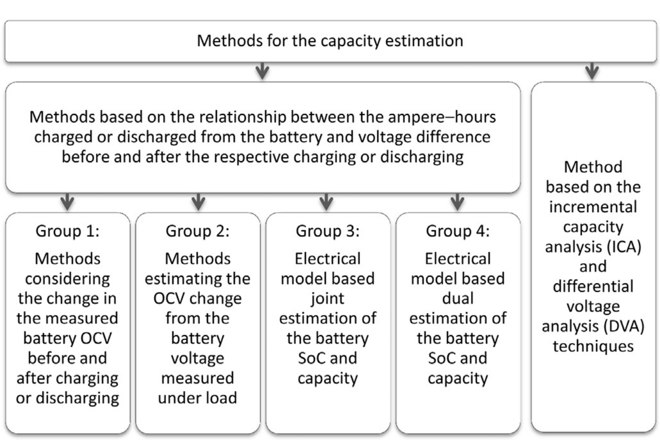

Fig. 6. Classification of the methods for the capacity estimation.

The joint estimation is very similar to the dual estimation implemented by the methods from the fourth group. However, instead of only one, two adaptive filters are employed: one for the SoC estimation (and eventually for the estimation of other model states) and another for the estimation of the capacity (and eventually for the estimation of other model parameters). Both filters can use identical or different techniques. In Refs. [67,71,72,78,100,264], the dual EKF and, in Ref. [263], the dual SPKF are employed. The SoC is supposed to be estimated by any KF and capacity is estimated by the RLS algorithm in Ref. [265]. In Ref. [266], the dual-mode sliding observer and, in Ref. [131], the PF is employed to estimate both the capacity and SoC. The combination of the KF and subspace parameter estimation method is proposed in Refs. [48,267,268]. In Ref. [267], the combination of the sliding mode observer and subspace parameter estimation method is additionally considered. The advantage of dual estimation over joint estimation is the lower demand on computing power: even though two adaptive filters are required, the dimensions of the respective model matrixes are lower. Similar to the joint estimation, the battery model must be very accurate to precisely estimate the SoC and battery capacity. Not only the battery capacity but also other model parameters must be implemented in a way so as to be adaptable to the aging state of the battery. Therefore, the complexity of the method is still high.

A simplified dual estimation with the EKF is proposed in Ref. [264]. Instead of incorporating the battery capacity as a parameter into the battery model, a separate model for the battery capacity is employed. It is based on a simple ampere-hour counter and requires the SoC as an input. The SoC is estimated by the first KF, and the capacity is estimated by the second KF. The second KF has very low complexity because of the simple model employed for the battery capacity. However, for an accurate SoC estimation by the first KF, the parameters of the full battery model must be adaptable to the aging state of the battery. This necessitates additional KFs or other methods for parameter adaption.

To avoid the need for a complex battery model, the change in the battery voltage required for the capacity estimation might be observed only under special conditions. In Ref. [269], for example, the change in the battery voltage during constant current charging is employed. Comparing the measured voltage curve with the parameterized charging voltage curve of the new battery, the capacity loss (and thus the present capacity) is determined. This technique is suitable for BEVs if they are always (or often) charged using the same charging procedure. In the vehicle-to-grid scenario, for example, this method cannot be always applied because the battery might be charged discontinuously with different currents, or it might be partially discharged in between.

The approach remarkably different from those described above is based on the incremental capacity analysis (ICA) and differential voltage analysis (DVA) techniques. The ICA together with the DVA are quantitative approaches to investigate inner chemical reaction and capacity fade of lithium-ion batteries. After cell relaxation and measurement of close-to-equilibrium open-circuit-voltage (cte-OCV) the evolution of IC curves allows investigating gradual changes in the electrochemical properties. The different plateaus and voltage gradients of the charge–voltage (Q–V) curves are directly linked onto dQ/dV peaks with different amplitudes of the IC curves. The DVA is calculated to emphasize different voltage areas by its derivative with respect to capacity (for cathode as well as anode side). A peak in the generated DVA spectrum then indicates a fast change in voltage. In Refs. [270–274] these characteristic peak changes in time and amplitude are investigated during the battery lifetime. It is shown that decrease of anode capacity causes a decrease of peak distance in DVA. In order to detect the peaks it is necessary to charge

and discharge the cell with a low current rate to avoid the superposition of the charge-transfer related overpotential over changes in anode potential and introduced for on-line BMS in Ref. [275] by applying a SVM parameter identification for Q–V curve fitting. In order to obtain the characteristic peaks the differentiation of the curve is carried out and compared to the initial curve. However, the authors take critical assumptions, such as the possibility of constant current charging and discharging phases in PHEV/EV application.

5. Methods for the estimation of the battery impedance

As the battery capacity, the impedance parameters of the battery in a new state are mainly defined by the battery design, but changes significantly over the lifetime due to aging processes. The knowledge of the present battery impedance parameters is mainly required for

1) estimation of the energy losses in the battery during the operation,
2) SoC estimation based on electrical models (Section 3.3.1), and
3) prediction of the available power of the battery.

Especially for the latest task the impedance parameters must be determined very accurate including their dependence on the current [23]. All methods for the estimation of the battery impedance can be divided into the three groups (Fig. 7).

1) Methods that estimate battery impedance at various frequencies and employ impedance spectroscopy and other related methods (Section 5.1).
2) Methods that use the representation of the battery in the form of an electrical model and estimate the parameters of this model in the time domain (Section 5.2).
3) Methods that use the representation of the battery in the form of an electrochemical model and estimate the parameters of this model (Section 5.3).

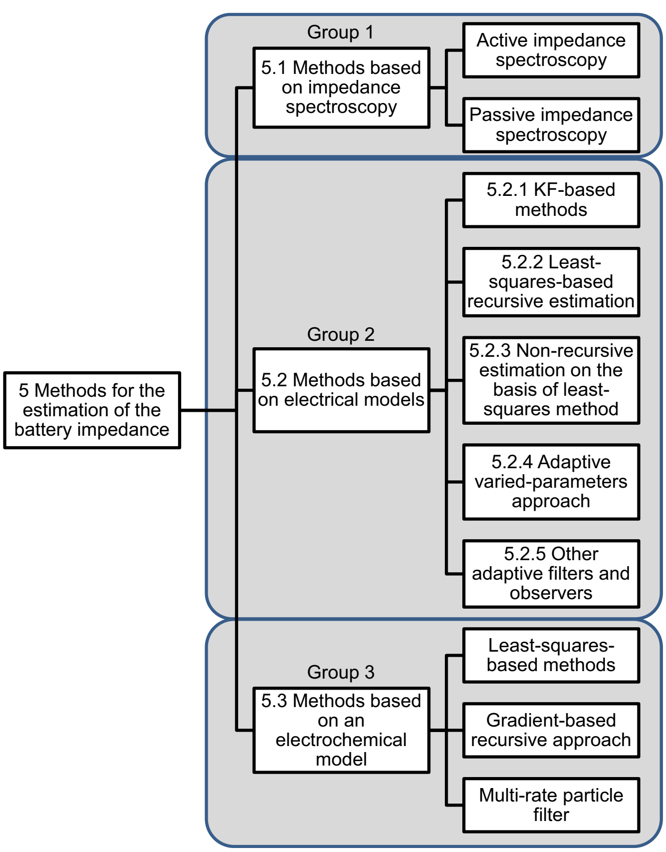

Fig. 7. Classification of the methods for the estimation of the battery impedance.

In addition to academic publications, there are a number of patents and patent applications (for example, in Refs. [276–278]) that claim basic ideas for determination of the battery resistance by considering the change in the terminal current and voltage of the battery under load. Only the battery resistance as a single value can be determined using this technique. More complex impedance parameters as well as their current dependencies cannot be estimated.

5.1. Methods based on impedance spectroscopy

Impedance spectroscopy is a commonly used method to investigate battery impedance in the laboratory. On the basis of this technique, some approaches are proposed to monitor batteries in the field [191,279–281]. Unfortunately, these methods require special circuits for active signal generation, which result in additional costs.

To avoid these costs, a passive impedance spectroscopy method is developed in Refs. [4,187,282,283] for LABs and applied, for example, in Ref. [284] for LIBs. Instead of the active generation of the required excitation signal, the current fluctuations caused by the battery load are used. The disadvantage is that these fluctuations must be periodic and significant in a certain frequency range used for the calculation of the battery impedance. This condition might be not fulfilled in a particular application. Furthermore, this method is not suitable for the determination of the current dependence of the battery resistance because of the usage of linear filters.

5.2. Methods based on electrical models

As described in Section 3.3.1, electrical battery models are often employed for the estimation of the SoC. The respective approaches including adaptive filters, observers, and other estimators can be extended to estimate not only the battery states but also the impedance parameters of the employed battery model. The model can then be directly used to estimate the available power of the battery. This link to the power estimation is the advantage of model-based impedance estimation. However, as shown below, the majority of the approaches and implementations proposed in the literature do not consider the current dependence of the battery impedance at all.

5.2.1. KF-based methods

Dual and joint KFs can be used not only for the SoC and capacity estimation (Section 4) but also for on-line estimation of impedance parameters of the battery model. In Refs. [78,264,285], the dual EKF, in Refs. [76,115,117,286,287], the joint EKF, in Refs. [263,288], the dual SPKF, in Ref. [107], the joint SPKF, in Ref. [58], the dual simple KF, and, in Ref. [289], the dual simple KF–SPKF are employed. These implementations differ mainly by the type and complexity of the battery model used. The general advantages and disadvantages of joint and dual KFs described in Section 4 are also valid for the estimation of the battery impedance parameters.

The SoC is supposed to be known and only one extended Kalman filter is used to estimate the pure ohmic resistance of the battery in Ref. [290]. The advantage of this method is its quite low demand on computing power. The disadvantage is that only pure

ohmic resistance is determined while other four battery impedance parameters of the employed battery model are supposed to be constant over the battery lifetime.

The common disadvantage of all implementations mentioned above regarding impedance estimation is that the impedance part of all models employed is linear. This means that the current dependence of the battery charge transfer resistance [23] is not considered. The current dependence is considered in Ref. [291] for a LAB incorporating the Butler–Volmer equation in the battery model and applying the EKF for the parameter estimation. However, the battery dynamic and current dependence are assumed to be unchanged over the battery lifetime. Only resistances in the battery model are updated on-line. This assumption does not fit the behavior of LIBs. As shown in Ref. [23], not only the battery resistances but also the current dependencies of the charge transfer resistance and double-layer capacitance change significantly over the battery lifetime.

5.2.2. Least-squares-based recursive estimation

Estimation of the battery model parameters based on the least-squares recursive approach has been often used in the literature in recent years and can be found in Refs. [15,123,153,164,249,292–309]. Various models with different grades of complexity are used in these publications. The employed variations of the estimation method are the RLS filter, recursive least mean squares (LMS) filter, and weighted RLS filter (WRLS).

The common advantage of this approach over the joint or dual estimation approach using the KF is the significantly lower demand on computing power because no complex matrix calculations such as inversions are required. In addition, the recursive algorithms do not require storage of a significant amount of data; therefore, they have low memory consumption on the target microcontroller. The first disadvantage is that the filters may be adversely affected by significant divergence problems when the battery model inaccurately reproduces the behavior of the battery. The second disadvantage is that all methods (except those given in Refs. [15,298]) do not consider the current dependence of the battery charge transfer resistance.

In Refs. [15,298], the nonlinearity of the battery impedance is proposed to be considered by employing many model instances with the RLS algorithm for different current ranges. However, in Ref. [15], this technique is shown to work reliably only with a maximum of three current ranges so that the current dependence is considered widely inaccurate and still vague. Furthermore, how the current dependence can be considered if the real measured current and voltage have to be filtered by high-pass filters, which are used in the implementation and influence the nonlinearity, is not investigated.

A moving window least-squares filter is employed for the joint estimation of the SoC and battery impedance parameters in Refs. [167,168]. Compared to the RLS, LMS, and WRLS filters, this method offers better stability and has potentially less divergence problems. This is achieved, however, at the expense of higher demand on computing power and memory consumption for intermediate storage of the measured data.

5.2.3. Non-recursive estimation on the basis of least-squares method

The main idea of non-recursive estimation is to measure the battery current and voltage over a certain period of time, store these data in the memory, and apply an iterative, least-squares optimization procedure to fit the battery model to the measured data. As a result, the model parameters are determined. This method, often used in the laboratory, is employed in Refs. [310,311] to monitor a LAB in a conventional vehicle. In Ref. [312], it is proposed to monitor a LIB. The advantage of the non-recursive estimation is that the battery model can be highly nonlinear [310] or even fractional [311]. The other advantage is high stability and accuracy because parameters are searched on a batch of data simultaneously. The disadvantage is a high demand on the memory and computing power for the iterative parameter search. All above-mentioned publications do not propose an efficient algorithm to overcome this disadvantage.

5.2.4. Adaptive varied-parameters approach

In Ref. [313] a method, called adaptive varied-parameters approach, that estimates battery impedance parameters including current dependence of the charge-transfer resistance is presented. The advantage of the method is that all parameters of the employed impedance model are estimated on-line including the parameter responsible for the current dependence of the charge-transfer resistance. It enables an accurate prediction of the battery voltage under load at even low temperatures and various aging states. The method is demonstrated to be implementable on a low-cost 16-bit microcontroller. The disadvantage is that for the consideration of the battery diffusion parameters an additional method is required.

5.2.5. Other adaptive filters and observers

In addition to the KF- and least-squares-based methods, other observers and adaptive filters known from control theory as enabling the recursive estimation of model parameters are proposed. In Refs. [314,315], a linear adaptive filter, in Refs. [48,266], a sliding mode observer, in Refs. [152,316], an observer based on the Lyapunov-stability criteria, and, in Ref. [317], a recursive penalized wavelet estimator are employed. These approaches are comparable to least-squares-based recursive methods and have the same advantages and disadvantages.

A simple EKF is combined with the statistical analysis of voltage pattern (SAVP) method to estimate the battery SoC and resistance in Ref. [69]. In the battery model used in the above-referenced publication, only the value of a single resistance, called the diffusion resistance, is assumed to change over the battery lifetime. This assumption may be satisfactory for the SoC and, eventually, the SoH calculations, but it is inappropriate for an accurate power calculation or prediction. The other disadvantage is that the SAVP algorithm requires current and voltage profiles to be stored in the memory for over 300 s, according to [69]. This limits the use of the algorithm on a low-cost microcontroller with only a few kilobytes of RAM.

In Refs. [318,319], a number of discharging–charging voltage patterns (DCVPs) and associated battery parameters are proposed to be stored in the BMS. These DCVPs and respective parameters are determined off-line in the laboratory for the battery at various aging states. The monitoring algorithm selects on-line the most suitable DCVP using DCVP recognition based on a Hamming network. The respective model parameters are then used for the model-based SoC estimation. This technique permits only rough determination of the most suitable battery model parameters because only few DCVPs can be efficiently used. This is sufficient for the SoC estimation but inappropriate when the battery model has to be used for the power prediction. Furthermore, extensive laboratory investigations are required to obtain a number of representative DCVPs and the respective model parameters.

A similar approach is proposed in Refs. [320,321] for a LABs. A number of “nominal models” (models with different parameters) are predefined and stored in the BMS. An on-line algorithm selects the most appropriate model employing a special model validation method.

In Refs. [154,155] a particle-swarm-optimization-based identification algorithm is proposed to estimate battery impedance

parameters. The employed impedance model is linear, but the method is also potentially applicable on nonlinear models. The disadvantage of the method is that it requires an intermediate storage of measured battery data and has a high demand on computing power. This limits the use of the algorithm on a low-cost microcontroller.

A structured neural network (SNN) is employed to estimate the pure ohmic resistance of the battery in Ref. [290]. In contrast to ANN based methods, the SNN method combines the battery model and the neural network based approach. The advantage is the high computational speed of the method. Disadvantages are the need for a large amount of training data and that only the pure ohmic resistance is estimated on-line while other four battery impedance parameters of the employed battery model are supposed to be constant over the battery lifetime.

In Refs. [97,98] a method for updating of the battery impedance parameters used in ECM- and EKF-based SoC estimator is proposed. The method, however, requires the discharging of the battery between 92% and 15% of SoC with a constant current, which practically never occurs in real applications.

5.3. Methods based on an electrochemical model

In Refs. [178,322], an electrochemical model in combination with the SPKF is proposed to estimate the battery SoC. In addition, a least-squares approach is employed to estimate the change in two model parameters. One of the parameters is the electrolyte conductivity. Changes in this parameter are proposed for the determination of the change in the battery resistance.

Another electrochemical model in the form of partial differential equations (PDE) is combined with the back-stepping PDE state estimator, Padé-based identifier, and nonlinear least-squares method in Refs. [181–183]. It allows simultaneous state (including SoC) and parameter (including battery resistance) estimation.

An electrochemical-based control-oriented single-particle model is employed in Ref. [323]. It is converted to the transfer function using third-order Padé approximation. The parameters of the transfer function are then estimated on-line employing a gradient-based recursive approach. It permits tracking the changes in the battery total resistance and diffusion time parameter.

In Ref. [184], an electrochemical model is combined with a multi-rate particle filter for simultaneous SoC and parameter estimation. However, from all model parameters, only two diffusion coefficients are implemented in an adaptable manner.

These all four approaches are not sufficiently described regarding their applicability for on-line estimation of battery parameters with realistic battery loads. The calculations required by the employed electrochemical models and adaptive estimators are very complex. Their implementation on a low-cost microcontroller is questionable. Furthermore, it is questionable how the results can be used for the estimation of the available battery power, which is one of the main reasons for impedance estimation.

6. Methods for the prediction of the available power

For EV applications, batteries must not only deliver a certain amount of energy to the drive train during operation but also provide a certain power in various situations. The power of the battery can be limited by the voltage, current, SoC, and temperature ranges allowed for safe operation. Since batteries are complex electrochemical devices, their power capability depends on a variety of internal and external conditions: temperature, SoC, and previous load history. In addition, it significantly changes over the battery lifetime because of aging.

For the EMS operating in EVs, knowing the maximum power that can be applied to and from the battery by charging or discharging, respectively, is essential. Knowledge about the available discharge power is used by the EMS to prevent the need for a sudden power drop. Such a need may occur, for example, during acceleration if the applied power is very high so that the battery very quickly reaches the limits of its SOA. Without power prediction, the EMS could therefore be obliged to rapidly reduce the power, leading to slower acceleration. For the driver, such unexpected vehicle behavior could even lead to a dangerous driving situation. If the BMS indicates the available discharge power to the EMS, then the acceleration rate can be limited from the beginning and, if required, slowly reduced later.

Knowledge about the available charging power helps the EMS to precisely control energy recuperation and its dissipation in mechanical brakes during deceleration. This is a precondition for intensive recuperation with minimized energy loses.

Since both events—acceleration and deceleration—function over a certain period of time, the power available for charging and discharging the battery over a given certain period of time must be predicted. The prediction horizon depends on the strategy of the EMS and is typically between 1 and 20 s.

Most of the existing techniques for the prediction of the available power can be divided into the two following two groups: methods based on a characteristic map and on a dynamic battery model. There is also one ANFIS-based method.

6.1. Methods based on a characteristic map

The methods based on a characteristic map use the static interdependence that exists among the available power of the battery, battery states (for example, SoC, temperature, and voltage), and power pulse parameters (for example, the duration of the power pulse). These dependencies are stored in the form of a characteristic map [25,324–326] in a non-volatile memory of the BMS and used for the prediction of the available power. The initial parameterization of the characteristic map can be performed in the laboratory. Test procedures for the battery pulse power characterization, as defined in various manuals and standards [327–330], can be employed. Since battery characteristics change over the battery lifetime because of aging, on-line adaption of the characteristic map is required. For this, the predicted power is compared with the measured available power. The difference between them is used to adapt the respective reference point in the characteristic map. As a result, the future prediction of the available power in this operating point is more accurate.

The main advantages of the methods from this first group are their simplicity and straight forward implementation. The first disadvantage is that only static battery characteristics are considered. If a very dynamic load is applied to the battery, then the available power may depend very strongly on the previous load history because of various polarization overvoltages in the battery. Since these overvoltages are not taken into account, the accuracy of the power prediction is very low. The other disadvantage relates to the adaption technique. If the maximal available power has to be predicted, then the respective characteristic map can be adapted only when this maximum power is in reality applied to the battery. Otherwise, the comparison between the prediction and measurement is not possible and, in consequence, the adaption cannot be performed. It limits the adaption rate in applications where the maximum power is applied to the battery very infrequently so that there are only very few opportunities for parameter adaption during normal operation. The third disadvantage is the need for storing the multidimensional characteristic map. The characteristic map requires a significant amount of non-volatile memory that

may be not available on a low-cost target microcontroller. This problem can be overcome by an approximation of the characteristic map with one or more empirical functions [325,326]. In this case, only a few parameters of these functions have to be stored in the memory. The disadvantage is that the adaption procedure becomes complex.

6.2. Methods based on a dynamic battery model

If the behavior of the battery can be modeled employing a dynamic battery model very accurately, then the available power can be also predicted very accurately. The existing methods (Table 3) differ in the type of models used and in other aspects. The important feature that must be implemented additionally is the on-line adaption of model parameters to the present aging state of the battery. An overview of adaption techniques can be found in Section 5.2. The need for on-line parameter adaption prevents the use of very complex battery models, but the complexity must be sufficient for an accurate power prediction.

In general, the model-based prediction of the available power is the most promising approach. It accurately considers the dynamic behavior of the battery; therefore, it can be applied by very dynamic loads. Unfortunately, battery models employed in existing implementations (except in Ref. [337]) do not consider the important aspect of current dependence of the battery resistance. As shown in Ref. [23], the current dependence can be neglected for new cells and at room temperatures, but it is considerable at lower temperatures as well as for aged cells. The promising results shown in the above-mentioned works are always obtained at room temperatures and by applying the proposed algorithms on new cells. However, the prediction of the available power plays a more significant role at lower temperatures and for aged batteries because the battery will more readily reach the power limit under these conditions. Therefore, algorithms must be able to deliver accurate results and must be verified under these unfavorable conditions.

The current dependence is explicitly considered in Ref. [337] and is implemented fully adaptable based on the varied-parameters-based approach (Section 5.2.4). It results in a sufficiently accurate prediction of the available power even at low temperatures. The only disadvantage is that the diffusion effects are not considered that results in a higher inaccuracy at very low SoC.

The other aspect that must be considered, when the model-based approach is used, is that a large number of cells are connected in series in a battery pack. Each cell might have slightly different characteristics and a different SoC, especially in an aged state [338]. As a result, the available power of each individual cell can be different and available power of the total battery pack must be calculated considering each individual cell. Some authors [333,335] propose using the battery model separately for each cell in a battery pack. The disadvantage is that high computing power is required because a plurality of model instances and their parameters must be calculated.

A different solution is presented in Ref. [337]. A sophisticated battery model is used only for the total battery pack. The differences between individual cells are considered by relative cell resistances and by implicit consideration of different SoC of individual cells. The advantage of this approach is the low demand on computing power and memory by sufficient accuracy of the total method.

6.3. ANFIS-based method

In Refs. [339,340] an ANFIS-based method for the prediction of the battery voltage is proposed to be a basis of the prediction of battery power. For the back-propagation the Levenberg–Marquardt method is applied, which combines the Gauss-Newton method (GN) with the gradient decent (GD) while for the feed forward parameter prediction the least-squares estimation is used to adapt the network to the current battery aging state. The problem of overfitting is counteracted by the use of a feature grid filter which adjusts the training parameter accordingly. However, for the battery power estimation additional low-pass filtering is needed to generate adequate ANFIS training pulses. Also, the real-time applicability was proven on rapid control prototyping (RCP) hardware instead on a microcontroller.

7. Methods for the SoH estimation

The capability of the battery to store energy and provide a certain power decreases over the battery lifetime because of aging. As an indicator for this deterioration, the other battery state—SoH—is defined. The most common understanding is that the battery SoH is 100% when the battery is new and 0% when the capability of the battery to store energy or provide power decreases to a certain minimum level. In HEVs, the SoH related to the battery power capability (SoH_P) plays the most important role, while in plug-in hybrid EVs and BEVs, both the SoH_P and SoH related to the

Table 3
Referenced works employing model-based approach for the prediction of the available power.

References	Description of the employed model	Is the adaption of the model parameters to the present aging state of the battery considered?	Is the current dependence of the battery impedance considered?	Are differences among individual cells in the battery pack considered?
[89]	ECM including series connection of the OCV element, resistance, and RC element[a]	No	No	No
[298]		Yes	Yes, simplified	No
[307]		Yes	No	No
[335]		No	No	Yes
[337]		Yes	Yes	Yes
[308]	ECM including series connection of the OCV element, resistance, and many RC elements	Yes	No	No
[314,315]	1st order digital filter	Yes	No	No
[331]	ECM including series connection of the OCV element, resistance, and RC element	Yes	No	No
[332]		Yes	No	No
[333,334]	Enhanced self-correcting cell model from Ref. [39]	No	No	Yes
[336]	ECM including series connection of the OCV element, resistance, and an element consisting of the parallel connection of the capacitance and two resistances	Yes	No	No

[a] RC element is a parallel connection of a resistance and a capacitance.

battery energy capability (SoH_E) are important indicators of the capability of the battery to perform its function. SoH_P and SoH_E can be estimated separately. As a common result, the minimum of the SoH_E and SoH_P can be considered.

In general, as indicators of the energy and power capability of the battery, the battery capacity and impedance, respectively, are evaluated. In this case, the determination of the battery SoH can be reduced to the determination of the present capacity and impedance. In HEVs and BEVs, this is also obviously the preferred way because the battery capacity and impedance parameters have to be determined anyway for the estimation of the residual energy and prediction of the available power. The SoH is 0% when the battery capacity decreases to a certain level (often defined as 80% of the nominal capacity) or battery resistance increases by a certain factor (often defined as doubling of the battery resistance). This SoH definition is somewhat equivocal because both the capacity and resistance can be defined differently, which results in different SoH values. However, often even more vague definitions of the SoH are used for conforming them to the applied methods for on-line SoH determination.

It should be noted that a SoH of 0% does not mean that the battery cannot be used further. The designation merely indicates that the battery has reached the predefined criteria for replacement. However, a significant change in battery characteristics might also be an indicator for an increased probability of battery failure.

As mentioned above, the estimation of the battery SOH can be reduced to the determination of the battery capacity and/or impedance depending on the employed SoH definition. As a result, the methods for the estimation of the present battery capacity described in Section 4 can be used as a basis for the SoH estimation when the SoH is defined as a figure of merit reflecting the capability of the battery to store energy (SoH_E). In addition, the methods for the estimation of battery impedance described in Section 5 can be used as a basis for the SoH estimation when the SoH is defined as a figure of merit reflecting the capability of the battery to provide a certain power (SoH_P). Because of these clear SoH definitions, this is generally the preferred way for estimating the SoH in HEVs and BEVs.

Unfortunately, the estimation of the battery capacity, and, therefore, of the SoH_E, might be a very challenging task. As a result, some authors propose to determine the capacity fade by employing its correlation with the increase in battery resistance. This approach can be considered as an attempt to define a universal SoH that would reflect both the change in the battery impedance and capacity. Various studies on lead-acid batteries [193,341–345] and some studies on LIBs [346] show that there are certainly some correlations, but the capacity fade cannot be determined exactly by considering only the change in the battery impedance. Another disadvantage is that extensive laboratory investigations are required to determine the correlation function.

There are also some other methods proposed for the estimation of the battery SoH without explicit estimation of the battery capacity or particular impedance parameters:

1) Methods employed in Refs. [347–352] are based on the measurement of the absolute voltage or voltage drop when a certain load is applied. The approaches are very similar to the estimation of the battery resistance; therefore, the result reflects the power capability of the battery (SoH_P).
2) In Refs. [198–200,220,353–356], the fuzzy logic method is employed. As inputs, the measured impedance parameters and/or other measured or calculated battery characteristics are used. The resulting SoH does not represent the change in the particular battery characteristic or capability, but the estimation of the general state of the battery and its classification as rather new, slightly aged, or at the end of life.
3) A completely different approach is employed in Refs. [357,358]. Instead of measuring battery characteristics in a present battery state and using them for the SoH estimation, the battery conditions (such as temperature, number of load cycles, accumulated ampere-hours) are observed over the battery lifetime. On the basis of these conditions and by employing a lifetime model, the battery SoH, capacity fade, and/or impedance increase are estimated. As a lifetime model, the recursive neuronal network and SVM are used in Refs. [357,358], respectively. Both require extensive off-line training. For this, laboratory investigations including accelerated aging tests are performed. Whether the lifetime model trained on accelerated aging tests can be accurate under real conditions is questionable. Therefore, these methods can only be applied as a good extension to other SoH estimation methods or as a basis for the RUL estimation, as described in the next section.

8. Methods for the estimation of the remaining useful life (RUL)

Under the parameter of RUL, the remaining time or number of load cycles until the battery reaches a SoH of 0% is understood. There are basically two concepts for the estimation of the battery RUL that can be found in the literature. The first concept (Fig. 8a) is based on the lifetime model used for the SoH estimation, as described in previous section. By using this lifetime model, predicting the battery RUL when the future battery conditions and loads are taken as inputs is possible. To estimate these future conditions, the observation of the battery usage in the last predefined period of time can be employed. Alternatively, a predefined reference load profile can be used [358]. The disadvantage of this concept is that it relies completely on the absolute accuracy of the lifetime model and does not include any recalibration mechanism

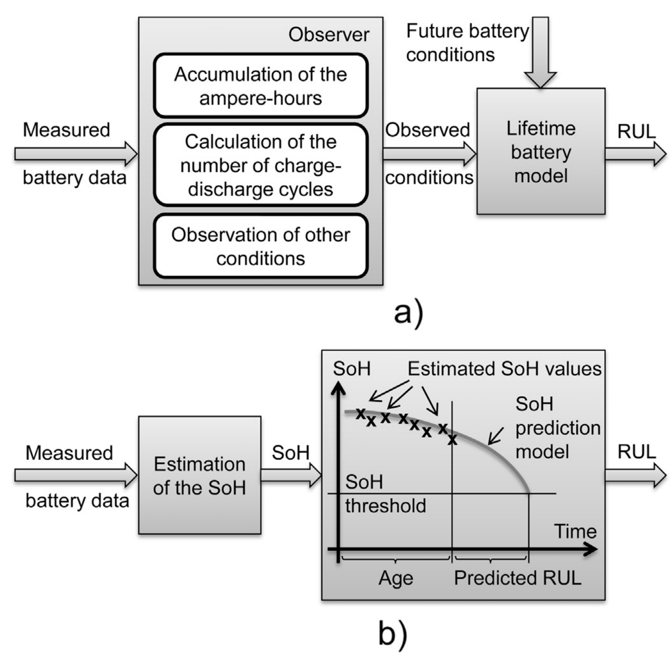

Fig. 8. Two concepts for the prediction of the battery RUL: a) the concept based on the observation of battery conditions and a lifetime model; b) the concept based on the SoH prediction model.

Table 4
Methods for the prediction of the RUL.

Method	References
Prediction based on the PF	[359–362]
Prediction based on the relevance vector machine (RVM) and a conditional three-parameter capacity degradation model	[363]
Prediction based on the support vector regression (SVR)	[364–366]
Prediction based on the combined RVM-PF approach	[367,368]
Prediction based on Dempster–Shafer theory and Bayesian Monte Carlo method	[369]
Prediction based on the least-squares regression method	[370]
Prediction based on the linear regression method	[371]
Prediction of the battery capacity after given number of full charge–discharge cycles based on an artificial fish swarm algorithm-based method with a variable population size (AFSAVP)	[372]

for consideration of the present battery SoH, the estimation of which is based on measurements.

The other concept (Fig. 8b) for the estimation of the battery RUL requires, in general, two parts. The first part is the estimation of the present battery characteristic that is selected as defining the battery lifetime. It can be battery capacity, impedance, their combination, or, in general, the estimated SoH based on measurements as discussed in the previous section. The second part is the prediction model that uses those characteristics as an input, analyzes its change in the past, and predicts its change in the future. The RUL is the predicted period of time until the characteristic will reach the threshold value defined as the end of life of the battery. Methods based on this approach are shown in Table 4. Additionally to the references in Table 4, in Ref. [373], the SVM and RVM approaches for the RUL prediction are compared and in Ref. [374], some of the methods are reviewed. The different prediction methods have their advantages and disadvantages regarding numerical complexity, accuracy, and the ability to produce not only the RUL estimation but also its confidence intervals. The main challenge, however, is the development and parameterization (training) of the employed prediction model that would allow the accurate prediction of the change rate of battery characteristics toward the end of life by considering their changes at the beginning of life. This prediction model can be implemented as a battery lifetime model that can be recalibrated employing presently measured battery characteristics.

9. Conclusion

In this paper, the methods for monitoring of the battery state of charge, capacity, impedance parameters, available power, state of health, and remaining useful life are reviewed with the focus on elaboration of their strengths and weaknesses. To this end, scientific and technical literature is studied and all approaches are classified in various groups.

There are a high number of methods for monitoring of the battery SoC. They differ significantly in the underlying approach, achievable accuracy and resulting complexity. However, a caution is advised when an appropriate technique is searched for a particular application since many of the proposed methods are only shown to work on new batteries. They have to be extended and qualified further to be able to deal with aged batteries and under real conditions.

There are also a high number of methods for estimation of the battery impedance. However, almost all of them are shown to work only at moderate temperatures and does not consider some effects substantial at only low temperatures such as current dependency of the battery resistance. This fact limits their application only for cases when only an average resistance and not exactly the resistance at certain current must be known. This is, for example, the case for the SoH estimation but inappropriate when the battery impedance is used for the prediction of the available power.

Much less methods are available for the estimation of the battery capacity. Furthermore, all of them use the same basic principle consisting in the determination of the relationship between the ampere-hours charged or discharged from the battery and voltage difference before and after the respective charging or discharging.

There are also only few usable methods for the determination of the available power of the battery. Most promising methods are based on electric battery model, include adaptive determination of battery impedance parameters and consider differences between single cells in the battery pack.

The estimation of the battery SoH can be generally reduced to the estimation of the present battery capacity and resistance and comparing them to the respective values of the new battery. For the prediction of the battery RUL some approaches can be found in the literature. The main challenge, thereby, is an accurate aging model that can be used as a basis for these methods.

In total, it can be concluded that a substantial number of approaches for the estimation of different battery states and parameters exist. The focus of further researches must be put on improvement of the methods and their extension to ensure their robust functioning in a wide temperature range including very low temperatures, under real load conditions, for aged batteries, and on low-cost target hardware.

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